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INTELLIGENT DATA REDUCTION FOR AUTONOMOUS POWER SYSTEMS

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ABSTRACT

Since 1984 Marshall Space Flight Center has been actively engaged in research and development concerning autonomous power systems. Much of the work in this domain has dealt with the development and application of knowledge-based or expert systems to perform tasks previously accomplished only through intensive human involvement. One such task is the health status monitoring of electrical power systems. Such monitoring is a manpower intensive task which is vital to mission success. The Hubble Space Telescope testbed and its associated NIckle Cadmium Battery Expert System (NICBES) have been designated as the system on which the initial proof of concept for intelligent power system monitoring will be established.

The key function performed by an engineer engaged in system monitoring is to analyze the raw telemetry data and identify from the whole only those elements which can be considered "significant." This function requires engineering expertise on the functionality of the system, the mode of operation and the efficient and effective reading of the telemetry data. Application of this expertise to extract the significant components of the data is referred to as data reduction. Such a function possesses characteristics which make it a prime candidate for the application of knowledge-based systems' technologies. This paper investigates such application and offers recommendations for the development of "intelligent" data reduction systems.

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INTRODUCTION

As the exploration of space continues missions become much more complex and much longer in duration. Future missions such as Space Station, spaced-based radar, communication and surveillance satellites, strategic defense initiative (SDI) systems and military aircraft will thus require more sophisticated and intricate electrical power systems (EPS) [8], [37]. Space power is an extremely precious resource. The fact that almost every subsystem, especially those that support the human elements for manned missions, is dependent on power plus the fact that space power has historically cost about $1000.00/KWH versus $.05 per terrestial KWH has placed space power high on NASA's priority list of research efforts. As was learned from Skylab, for which 15-18 ground support personnel were required to augment extensive crew involvement for an 8KW system, a major effort had to be directed toward autonomously managed electrical power systems.

Automating activities ordinarily performed by humans was seen as the primary means of reducing both airborne and ground support efforts and costs [9],[16],[36],[39]. Additionally, more fully autonomous power systems (as well as other subsystems) will be a necessity for deeper unmanned exploration of space where missions will require decisions and actions in "real-time". The time lags incurred with data transmission and remote intervention will not be acceptable in allocating and protecting the precious electrical power resources. In 1978, therefore, the Office of Aeronautics and Space Technology at NASA Headquarters directed NASA to undertake efforts towards accomplishing such autonomy. Since that directive various NASA efforts in conjunction with several contractors (including Martin Marietta, Rockwell/Rocketdyne, Boeing, TRW, Hughes and Ford Aerospace) and Universities (among them Auburn, University of Tennessee, Tennessee Tech.,University of Alabama-Huntsville,Vanderbilt and Carnegie Mellon) have made much progress in the realm of space power automation.

It was realized early on in power system investigations that autonomous systems would require a certain amount of embedded intelligence to supplement the already proven more conventional computer approaches [23]. Thus much of the current research effort is focussed on artificial intelligence techniques, namely application of expert and knowledge-based systems. The term "expert system" (ES) refers to a software system which performs a complex, well defined task using the same input information and problem solving strategies as a human expert. Additionally, an expert system possesses the capability to make accessible to the user the reasoning logic it uses to perform the task. It is implied that the expertise captured by such a system has its origins in the experience that one or more humans have accumulated while performing a given problem solving task. The term "knowledge-based system" (KBS) refers to a software system much like an expert system but which implements a body of problem solving knowledge which may come from any of several sources including text books, humans (in the form of expertise or more general experiential knowledge) or others.

It is important in the domain of space power system applications to draw the distinction between these two types of systems. The reason for this is that this is a very young domain and "experts" with experience managing space power systems do not exist. However, the experience of humans working in this arena coupled with more general knowledge about power subsystems and components make it possible to develop what for the purposes of this paper will be referred to as knowledge-based expert systems (KBES).

Though few doubt the important role that KBES approaches will play in space power automation the domain is one which offers more complex challenges than those to which the technology has already been successfully applied. One of the approaches to overcoming some of these challenges is the development and utilization of realistic autnomous power system breadboards and test beds on which KBES technologies can be developed and validated [3],[39]. Since space power systems involve new and highly dynamic technologies, it is through the development and subsequent use of testbeds that the necessary "engineering expertise" is being established and archived [18],[25]. Moreover, in order for autonomous power system development to proceed in a continuous manner researchers and developers must rely on the lower risk terrestial testbeds as opposed to actual mission experience alone.

The primary autonomous power system functions that have been identified for application of knowledge-based systems include: status estimation, system health status monitoring and maintenance, fault detection and management, dynamic load scheduling and mainatenance procedure advising [6]. Currently research and development is ongoing in almost all of these areas and proof of concept has been established by various prototype systems. One of the most crucial functions among these, since it is a first line defense against system or component failure, is the system health status monitoring. This is the latest area being researched for knowledge-based expert system applications.

During actual space missions, engineers must monitor the telemetry data from various power system sensor and identify and analyze any "significant findings." Siginificant findings are defined more deeply than those identified by most current systems; namely, the indication based on a single variable that a fault has occurred. Significant findings must be based on not only single variable values, but also on the interactions between the variables and the trends indicated by them. Such significant findings can indicate an imminent failure even though single variable analysis might not. Such a task will involve large amounts of data, only some of which (in many cases a very small percentage) will be relevant to any particular prediction. These factors, combined with the frequency and regularity of task performance, requires engineering expertise on the functionality of the system, the mode of operation, and the efficient and effective reading of the telemetry data. Such a function can be most effectively implemented using knowledge-based systems technologies [29]. The application of such technologies will result in intelligent systems to support the monitoring function.

The main purpose of this paper is to review the literature applicable to the intelligent health status monitoring domain. The findings of this review will then be synthesized into recommendations for the development of intelligent space power monitoring systems. The review is broadened beyond space power system monitoring because many of the problem characteristics exist in other domains such as human health monotiring, manufacturing system monitoring, test data analysis and others. One characteristic of all such problems, however, is the requirement to efficiently and effectively perform what is referred to as "data reduction." Data reduction in this context is defined as the process of extracting from the larger amounts of monitoring data (usually being provided by real-time sensors) only the "significant" elements and presenting these elements to the analyst in a form most conducive to supporting decision making concerning the heatlh status of a system. Reducing data to such a form usually involves the application of various statistical techniques such as graphing, plotting, calculating maximum and minimum values, calculating means, taking differences, determining trends, analyzing and comparing signatures, etc. The issue of intelligent data reduction has universal implications due to the amount of information now available to decision makers because of the advances in information processing and remote sensing technologies.

OBJECTIVES

The objective of this work is to investigate the application of knowledge-based system technologies to the field of space electrical power system health status monitoring. This objective was accomplished by first examining current applications for autonomous power systems with emphasis on the Hubble Space Telescope test bed and the Nickle Cadmium Battery Expert System - NICBES. Next a broad review of the literature related to knowledge-based monitoring systems employing intelligent data reduction techniques was conducted. In conjunction with the literature reviews, varous NASA and contractor personnel were contacted or interviewed concerning the topic. Finally, the findings were synthesized into recommendations for future research efforts in this domain.

BACKGROUND

Marshall Space Flight Center's Electrical Power Branch has been involved since 1984 with the development of expert or knowledge-based systems [38]. Attention has been primarily focused on comprehensive fault management and dynamic payload rescheduling activities. Comprehensive fault management includes identifying anomolies, diagnosing actual faults, recommending corrective action for fault recovery and autonomous implementation of fault recovery actions. The knowledge-based systems which have been developed and are being researched as part of these efforts include: the Fault Isolation Expert System (FIES I and FIES II) [38], the Space Station Experiment Scheduler (SSES) [39], the fault detection/diagnosis/recovery system (STARR) [34], the Space Station Module Power Management and Distribution (SSM/PMAD) system automation project [6], the coopertive expert system project for Scheduling and Fault Analysis/Recovery Integration (SAFARI) [38], the NIckle Cadmium Battery Expert System (NICBES) [4],[21],[26] and the latest research efforts for Intelligent Data Reduction - I-DARE [17]. I-DARE is primarily being developed to enhance and extend the functioning of NICBES which currently interfaces with the Hubble Space Telescope (HST) power system testbed. Since the research presented in this paper was conducted to support and extend the efforts of the I-DARE project a brief overview of the three interfacing systems will be provided. For more detail on the other efforts listed the reader is referred to the sited references.

The HST (Hubble Space Telescope) Testbed was developed to simulate as close as practical the actual system that is to be flown on the HST [3] (see Figure 1). The testbed consists of six major elements: (1) the power distribution breadboard, (2) the batteries, (3) the solar array simiulators (SAS), (4) the load banks, (5) the charge control hardware, and (6) a control computer (CC), a monitoring computer referred to as the Digital Data Acquisition System (DDAS), and a computer for the NICBES. The breadboard includes all pertinent components of the HST EPS. It provides switching for battery isolation, Solar Panel Array (SPA) switching and battery reconditioning, as well as monitoring via panel meters of individual battery voltage, current and temperature. Additionally, three strip chart recorders record voltage and current data.

Power storage is provided by six nickel cadmium batteires manufactured from the same lot as the actual flight hardware. During the sun portion of its orbit, the HST will be powered by 20 SPA's (three each per battery) which are simulated on the testbed by two adjustable constant current power supplies. Three independently controlled load banks simulate the spacecraft load and are controlled by the control computer. The charge control hardware consists of six

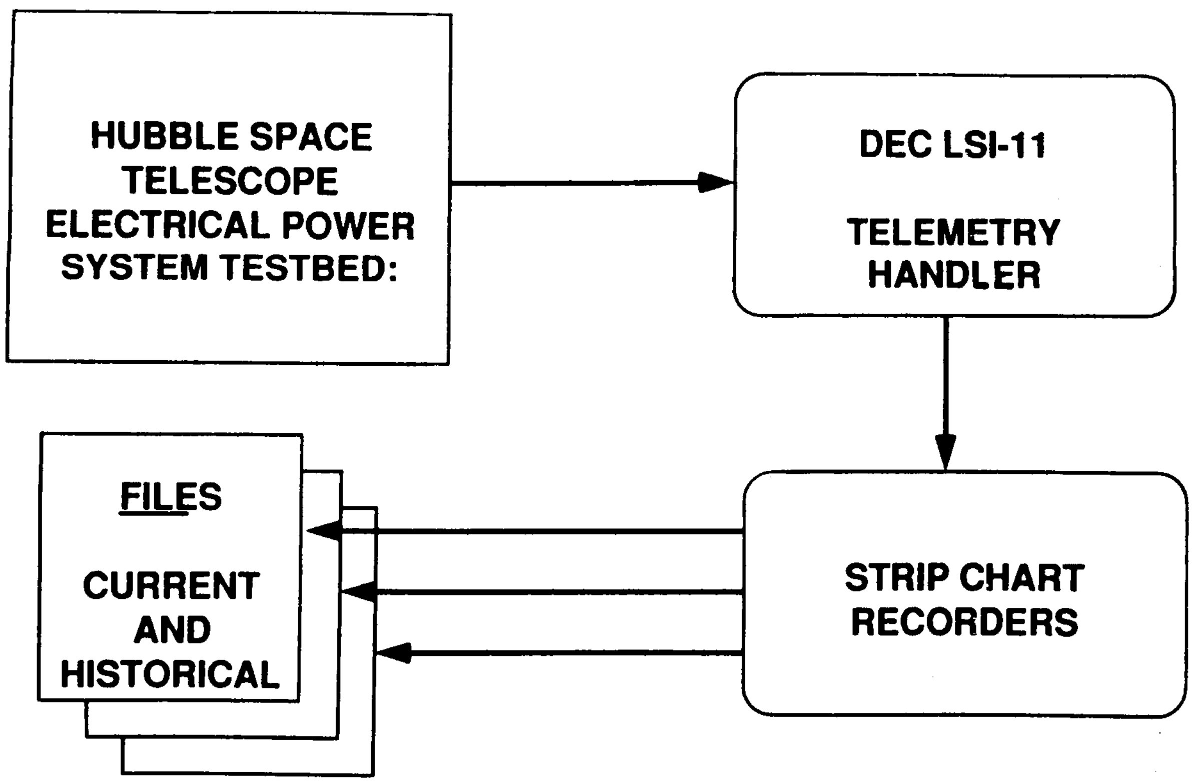

Figure 1 - HST Functional Diagram

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charge current controllers (CCC) identical in circuitry to the flight hardware. The Control Computer is a microprocessor based system designed and built at MSFC specifically for the breadboard. The Control Computer provides for keyboard entry, via a VDT, of several command adjustable parameters, thus providing functions such as: SAS control, CCC monitoring, and monitoring and control of load bank voltages, battery temperatures and battery voltages. The DDAS function is performed on a DEC LSI-11 computer and is responsible for data acquisition, limit checking, data summaries and orbit time control. The DDAS samples approximately 400 channels of incoming data from the breadboard. Once per minute it measures 138 cell voltages and pressures, currents for the six batteries and battery protection circuits, the three load voltages, six battery voltages and six temperatures per battery. The DDAS provides data summaries such as high/low reading, recharge ratio, depth of discharge, etc., on a per orbit basis. The third computer component of the testbed is currently as IBM PC/AT which is dedicated to the maintenance and functioning of the expert system, NICBES.

NICBES

The prototype of NICBES is currently integrated with the HST testbed and serves as a fault detction and diagnosis system and also a battery health management system [4] (see figure 2). Functionally NICBES has four modes: (1) fault diagnosis, (2) battery health status, (3) advice on battery maintenance, and (4) decision support aid. The prototype has two separate subsystems: a data handler and a diagnosis expert system. The data handler is written in Microsoft C and serves to receive the telemetry data from the DDAS and "massage" it into the form required by the diagnosis subsystem. The diagnosis subsystem is written in Arity PROLOG [26]. Its main function is to reason from the data provided by the data handler and determine if any exception situaitons are indicated. The engineer may initiate operation of the expert system once twelve orbits worth of data have been processed by the data handler. In addition to fault diagnosis which is based on the current state of the EPS, NICBES also monitors battery health status based on both current orbital data and historical data. Status analysis is accomplished based on the interactions of several variables. Based on an analysis of trends and averages for combinations of parameters maintenance procedures (i.e., battery reconditioning, charging scheme, etc.) are recommended. Finally, NICBES provides decision support to the user by supplying summary plots of pertinent data over the most current twelve simulated orbits.

The NICBES prototype has performed well over the past year and a half. During this period, however, several features have been identified for incorporation and upgrade of the system. Among these are: (1) the need for a user friendly rule editor, (2) a multitasking capability to allow data collection to continue while a NICBES consultation is in progress, (3) an expanded capability on the number of orbits of data which can be handled (upgrades from the current 12 to

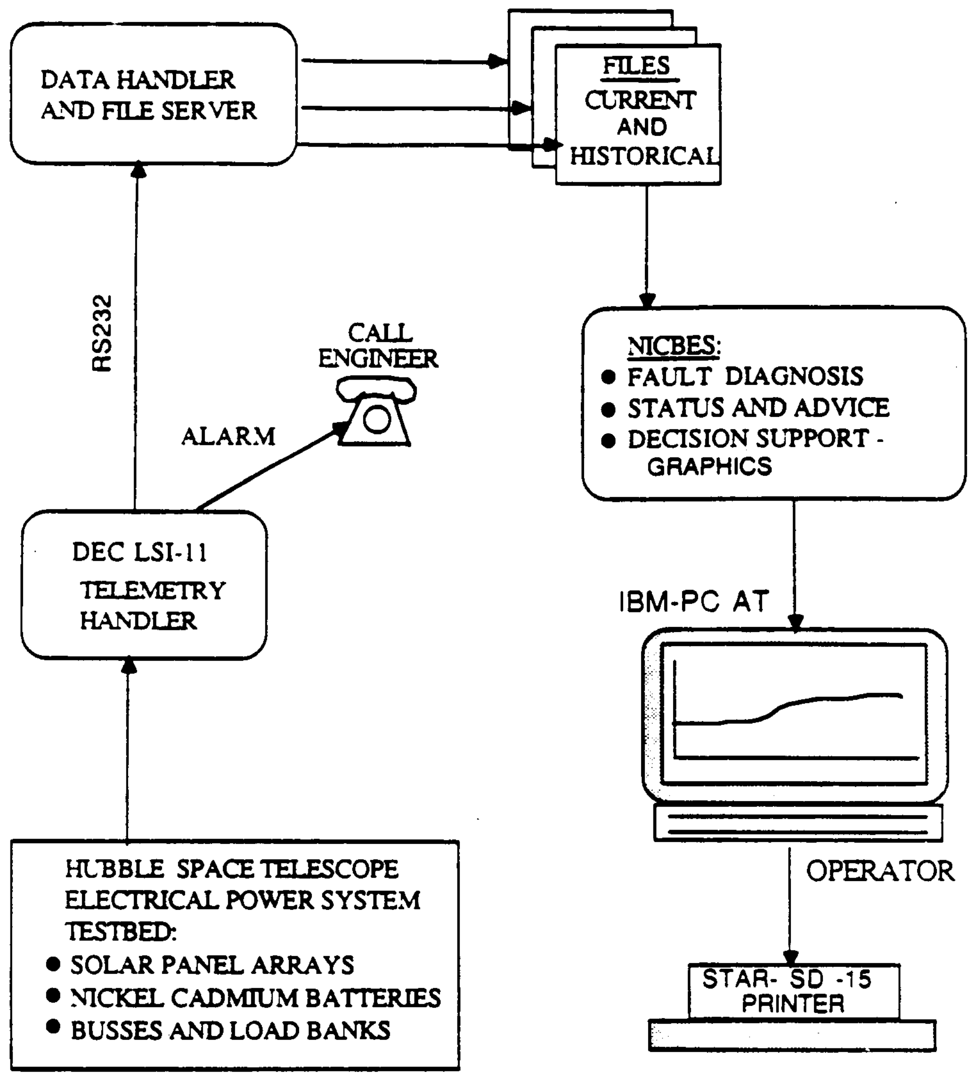

Figure 2 - NICBES Functional Diagram

perhaps 500 orbits have been discussed) (4) providing a capability to perform statistical prediction of battery life, and (5) the growth of NICBES into a model based system to explicitly capture the interelationships of the EPS and thus allow diagnosis of unforseen faults. All of these features are currently being researched and evaluated.

I-DARE

Data reduction takes many forms, the most common form is statistical reduction, i.e., means, moving averages, trend analysis, minimums and maximums, etc [1],[14],[32]. Though these are very useful for analyzing system performance further reduction which considers relationships between variables as well as system functioning lends support to an even deeper analysis. Such reduction brings more of a qualitative approach to the problem. This can be referred to as "intelligent" reduction. Intelligent because expertise is brought to bear on the problem through the reduction process and also because the data is refined by considering the interactions of the system being analyzed. The overall purpose of the I-DARE effort is to investigate the phenomenon of data reduction, determine the knowledge used in performing this task by humans and prototyping a system for incorporation into the HST testbed [17].

Currently the amount of data being received form the DEC LSI-11 included 370 values per minute. Since each orbit is ninety-six minutes in duration the orbital analysis must be performed on 35,520 values. Adding to the amount of data is the fact that 100 orbits of data are usually required for accurate trend analysis. Such analysis, therefore, must be based on 3,552,000 values. Complete analysis of such a quantity of data is a formidable task for anyone and is complicated even further when all the interrelationships are considered. The formidability of the monitoring task coupled with large demands on computer storage require advanced forms of intelligent data reduction to support engineers in reducing power system telemetry data to its significant components. The next section will provide a review and summary of the findings of current efforts in applying knowledge-based technologies to the health status monitoring function.

CURRENT KNOWLEDGE-BASED APPROACHES TO SYSTEM HEALTH STATUS MONITORING

Over the last three to four years several efforts have been undertaken to investigate and prototype knowledge-based systems for the health and status monitoring of space systems. This section will briefly review these efforts and summarize the finding. A thorough understanding of current system monitoring technologies and their approaches to data reduction is a necessary prerequisite to the design and implementation of effective data reduction techniques for further improving the monitoring function.

Siemens [30] has written several papers on a knowledge-based system, STARPLAN, which monitors telemetry data, alerts the operator if anomolous conditions are identified, and then functions to suggest corrective actions. STARPLAN was built using the KEE environment. KEE facilitated development of the knowledge base since the knowledge base consists of object descriptions which are reasoned about based on satellite telemetry. It performs fault diagnosis by utilizing relational links between objects of the domain model and the descriptions of the objects. It uses production rules only if the model-based approach fails.

Hamilton [22] implemented a system in LISP on a Symbolics 31670 which was called SCARES and was applied to the attitude control system of a spacecraft. SCARES was implemented with an object oriented approach using frame-based knowledge representations and inductive and deductive reasoning. It uses a three stage approach of monitoring, diagnosis and hypothesis generation and test to detect, diagnose and recover from anomolies. The monitoring is done by performing three types of checks on the telemetry: a limit check on individual telemetry points, a rate check on two or more telemetry paint on the same channel, and a cross-channel check for consistency. Rather than analyzing all the data, the monitor only receives a sample of each signal once every two seconds. These samples are sufficient to monitor and detect faults with real time performance.

Skapura and Zach [31] describe an OPS5 based system developed using LISP and designed to handle the front-end analysis of the telemetry stream received from the Space Shuttle. As a result of their investigation into application of knowledge-based systems for real-time analysis, they draw several important conclusions. They point out the problems encountered in attempting to use OPS5 for such applications. Specifically performance limitations, lack of interrupt handling facilities and the need for a multi-tasking architecture. The authors also point out as do Watson, Russell and Hackler [ ] that the RETE algorithm, designed to work in environments where the data changes slowly, is not optimal for real-time telemetry data analysis.

Gholdston Janik and Lane [20] report on a prototype expert system to aid in the evaluation of sensor data to monitor and predict power component performance and to identify faults. The system was developed on a Compag 80386 computer (with a 80387 co-processor) using the M1 rule-based development tool. As well as providing a rule-based language, M1 was also chosen for its ability to interface with the data acquisition, reduction and graphics routines which were done in C. The system is designed to operate in an automatic monitoring mode or an interactive diagnostic mode. During automatic monitoring mode, all EPS information is collected from the distributed processors and made available to the expert system through a data base. The expert system then determines if any of the data are exhibiting a failure mode.

Pooley, Thompson, Hamsley and Teoh [28] discuss the architecture of an intelligent health monitoring system (HMS) for reusable rocket engine systems. SEES, SPARTA Embedded Expert System, synergistically integrates vibration analysis, pattern recognition and communications theory techniques with AI techniques. The main component of the application is an expert system that uses confidence levels to resolve conflicts among compound data and thenheuristically chooses each data set and derives classification rules. The system is comprised of three major subsystems. The SEES Front End (SFE) processes raw data to screen obvious anomolies and derive the reduced data set from which it generates an appropriate signature (the authors do not detail the data screening, reduction and signature generation techniques since this information is considered propriety). The Embedded Expert System (EES) uses the information provided by the SFE and the rule set in its knowledge base to infer operating conditions, deduce mean time to failure and recommend maintenance schedules. The EES has the capability to invoke functions in the SFL for further data reduction. The expert system component is being developed using Rule Master which can then be integrated with the rest of the system which is developed in C. The Support Function Library (SFL) is a set of supporting functions for the rest of the HMS.

Watson, Russell and Hackler [36] report on the design and initial development efforts of the Diagnosis and Proection Expert System (DAPES), an expert system for the purpose of performing on-line diagnostics and parameter evaluation to determine potential or incipient fault conditions in electrical power systems. The system will be part of an overall monitoring computer hierarchy to provide a full evaluation of the status of the power system and react to both incipient and catastrophic faults. The attempt with DAPE is to provide as much computational intelligence as possible to the remote low-level machinery as possible. Such a capability is feasible with current advances in microprocessor hardware technologies. The authors' efforts are focused on the architecture of a responsive expert system for on-line monitoring environments.

To accomplish this responsiveness an expert system shell PMCLIPS was developed. PMCLIPS is a modification of CLIPS. It uses a Parallelized Match Algorithm (PMA) based on the RETE Algorithm. Though some of the internal data holding structures are similar for the two algorithms, the flow through the structures varies considerably. PMCLIPS takes advantage of the rapidly changing data and parallelism which characterize monitoring systems to enhance the system's responsiveness. Initial results indicate that significant speed up is accomplished. Prototyping and testing is continuing. Though the authors site data compression and detection of incipient faults as functions of DAPES, no detail is provided concerning these functions.

Doyle, Sellers and Atkinson [11] present an approach to monitoring referred to as "Predictive Monitoring" which is based on the idea that effective monitoring requires an explicit model of a device. The model requirement is based on (1) the fact that the nominal ranges associated with a sensor are dynamic as opposed to static as in traditional monitoring approaches, and (2) the fact that as space systems become more and more complex and sensors number in the thousands, they must be treated as resources and context-sensitive importance criteria should be used to determine when and how they should be sampled. Additionally, the authors feel that providing explanation for expected sensor values would speed up the diagnosis process.

A predictive modeling system called PREMON is proposed and is made up of three modules: (1) a Causal Simulator, (2) a Sensor Planner, and (3) a Sensor Interpreter. The causal simulator, based on a model of the system being monitored, generates predictions about the next cycle of behavior of the device. The model distinguishes different operating modes of the device and compliments traditional analytical models with qualitative reasoning capabilities to accommodate causal dependencies and incomplete and uncertain values. The Sensor Planner, given the predicted behavior, makes choices about what behavior to verify, which sensors to employ, and how the sensors should be sampled. The Sensor Planner then passes instructions to the Sensor Interpreter which reads sensor channels as directed and compares these with the expectations provided by the Causal Simulator. Expectations about behavior and knowledge about distinguishable qualitative values, which are derived from a device model, drive the comparison and recognition process.

Erickson and Rudakas [15] also report on the advantages to be gained from a model-based reasoning approach for knowledge-based application to monitoring and fault diagnosis systems. The paper discusses the two-phase development of a system called TEXSYS, Thermal Expert System, which was developed around the Space Station Thermal Testbed, SSTT (again illustrating the major importance of testbeds to the development of KBS components for autonomous systems). TEXSYS was first prototyped using KEE and SimKit on a Symbolics 3670. The phase II prototype employed MTK, the Ames Research Center's causal Model Toolkit, in place of SimKit. MTK was designated to overcome several technical issues raised during phase 1 development. Several key features of the TEXSYS system are worthy of mention.

The SSTT model which was developed using the object-oriented and frame-based representation of KEE was a simplified model of the testbed which incorporated domain experts' rules of thumb, as well as the relevant physical laws. Additionally, rather than using direct links, the model topology was represented using KEE CONNECTIONS which allowed representation of behavior at component boundaries. KEE worlds was used to represent different temporal states in distinct "worlds" thus providing a limited temporal reasoning facility. A hierarchical structure was employed to allow reasoning to progress from "black box" levels to subcomponent level. The ability to perform qualitative and quantitative modeling and reasoning, as well as the ability to deal with parameter uncertainty was provided by the structure of MTK. MTK allows for utilization of "Parameters" which represent the significant physical measurements employed in describing a given system (i.e., temperature, pressure, flow rate, etc.). Parameters are represented as special objects with Value, Best Value, State and History attributes. Values can be given or derived quantitative measures or ranges and can take on multiple values reflecting different chains of inference. Best Value represents the systems best guess of the "real value." The State is simply a qualitative symbolic value of a Parameter (i.e., NOMINAL, HIGH, NEGATIVE, etc.) and History, another symbolic value, captures time behavior such as INCREASING, STEADY or DECREASING.

The most current and perhaps most significant research efforts are those reported by various personnel at the Lockheed Artificial Intelligence Center [7], [12], [13]. Lockheed is the prime contractor for the Hubble Space Telescope, moreover, it is the HST Mission Operations Contractor responsible for the ground operations that ensure the health and safety of the vehicle. The primary means for assuring such operation is the effective monitoring of approximately 4,690 different telemetry monitors available for interpretation. Six workstations will be manned 24 hours a day by three shifts of operators during actual flight. The complexity of the HST and the massive amounts of telemetry data being received make system health status monitoring extremely difficult. Lockheed, therefore, has been actively engaged in applying KBS technologies to this domain. The main thrust of these efforts are directed toward development of the Telemetry Analysis Logic for Operating Spacecraft (TALOS) system.

TALOS is a knowledge-based system consisting of a multitasking architecture for performing real-time monitoring and off-line deep analysis. It is being developed using Lockheeds L*STAR proprietory shell. The system consists of three separate processes which run concurrently and communicate via message passing using a mailbox approach. The three processes are the Inference Process, the Data Management Process (DMP) and the I/O Process.

Telemetry data is first preprocessed by a VAX and is then sent to the DMP for scaling and compression before utilizaton by the Inferencing and I/O Processes. The Inference Process is written in C and has been designed to overcome certain deficiencies of other tools when applied to the monitoring domain. In order to reduce long run-time pattern matching searches, the rule compiler stores location information about triples in a uniform data structure created at compile time. There is also a context mechanism (context relating to mode of HST operation for example) which partitions rules to limit the number being examined for given situations. This context sensitivity allows "attention" to be focused when important events occur (i.e., the context may cause a rule to fire which increases the rate at which the DMP sends data on a particular monitor). The Inference Process uses special functions which reason about trends and statistics such as time averages and rates-of-change to provide temporal reasoning capabilities about past, present and future events. The Inference Process also contains the "knowledge" requird by the DMP and sends this intelligence as necesary via messages. The DMP needs to know for each telemetry monitor such things as sampling rate smoothing and scaling factors, limits, etc. These factors are dynamic based on the requirements as reflected in the knowledge base.

Also resident in the Inference Process are the diagnostic modules which are activated periodically to analyze archived telemetry data or automatically when non-nominal operation is indicated based on real-time telemetry analysis. Archived data is analyzed for anomolous behavior as well as adverse trends. For real-time analysis only about 400 of the over 4000 telemetry monitors are used by operators under normal operation. If non-nominal behavior is indicated, then rules fire in the knowledge base resulting in messages being sent to the DMP to request data collection from new monitors and/or changes in sampling rates or data compression techniques. The I/O Process is a hierarchy of dislays which can be traversed with a mouse. Mousing on a monitor displays a strip chart which is updated in real time by data from the DMP The I/O Process also receives status/health messages from the Inference Process.

Findings

A synthesis of the findings from the literature reviewed above leads to several important observations and conclusions concerning the effective application of knowledge-based technologies to system health status monitoring. Those which have relevance to the concept of data reduction and which should be considered in the implementation of reduction techniques in this domain are now reviewed.

New technologies and complex systems overburden analysts with telemetry data and make manual real-time or near real-time analysis infeasible. Automating portions of the monitoring process has proven feasible but traditional approaches of establishing a-priori static nominal ranges proves ineffective for most current applications where the changing contexts of the system dictate the nature of analysis and the data required to support this analyses. Sensors must be treated as information resources and managed accordingly. The context should dictate the what, when and how to monitor. One approach to accomplishing this is with a model-based system where an explicit system model which captures the causal relationships and dependencies is part of the knowledge base. The model expectations can then help drive the analysis.

Effective monitoring systems will have to possess reasoning capabilities beyond just quantitative reasoning. More specifically, qualitative and temporal reasoning are considered mandatory. Qualitative reasoning can accommodate uncertain missing and noisy data [19]. Additionally, the temporal relationships between system components and the data generated must be captured by the system. Trend detection and analysis are crucial to effective system health status monitoring.

Finally, the rapidly changing data inherent with space system monitoring dictates certain system characteristics. Systems must have interupt or multitasking capabilities. Moreover, the inferencing process must be freed of data management functions and I/O functions. This can be accomplished with a system architecture which provides for three separate modules which accomplish these tasks and communicate with each other as necessary. The rapidly changing data also requires new and innovative inferencing techniques to overcome the slow search and matching algorithms characteristic of most current KBS tools.

Implications for Intelligent Data Reduction

As stated previously, intelligent data reduction is the process of extracting from a set of data only those significant facts which the "expert(s)" deem necessary for the analysis being undertaken. The concern in this investigation was to determine the types of characteristics that might be deemed significant for the health status monitoring of space power systems and potential data reduction techniques capturing these characteristics. In considering data reduction techniques to support health status monitoring, one must also consider the operation of fault detection and diagnosis which often follows the monitoring function. One major distinction between these functions is the time frame for performance. Monitoring is something that must be done on a near real-time basis so that anomolies can be detected, or, better yet, predicted early enough to prevent further system contaminatin. It has been clearly shown that the efficiency of the monitoring process can be greatly improved by first performing data reduction on the telemetry data [5] [24] [28] [33].

Moreover, much of the information which would be considered significant for health status monitoring can also play a major role in anomaly identification. It has been shown that the most effective approaches to fault detection involve model-based expert systems. This same model-based system can be used to drive a data reduction module.

Causal modeling allows the interrelationships and dependencies of system components to be captured from both a physical system perspective (i.e., based on physical laws), as well as a conceptual perspective (based on the intuitive and heuristic knowledge of an expert) [2] [15] [35]. Such an approach also allows system contexts to be considered since the model can capture the various defined states in which the system will operate. Often as contexts change, the interrelationships of the model will change and vice-versa.

Data reduction techniques should reflect these relationships. For example, during battery charging, cell temperature is a telemetry value which needs to be closely monitored. Consequently, during a charge state, the temperature sensor data should be sampled more frequently than during a discharge state. Likewise, cell pressure which is related to temperature should also be monitored at a similar rate. Another advantage of the modeling approach is that it can provide a means of checking for telemetry data contamination or loss. The relationships which exist in the model can be used to predict or verify the various telemetry values. In terms of system structure for such an approach, a separation of reduction and inferencing functions is most appropriate. A library of reduction functions as specified by the analyst might be incorporated into the data handler and could receive and pass necessary information from and to the model-based inferencing module.

The hierarchical approach mentioned previously also has applications to the data reduction function. It would seem natural that as the monitoring function proceeds from broader (i.e., a conceptual black box level) to finer (i.e., subsystem or component level), levels of detail, the data reduction employed will also go to finer levels of detail (i.e., from a qualitative measure such as INCREASING to a more detailed and quantified trend analysis) [19]. At the conceptual level, overall battery readings might be monitored, whereas at a lower level, individual cell values would be of concern. The level of detail would again be influenced by the context as well as the model interactions.

CONCLUSIONS AND RECOMMENDATIONS

This research has clearly shown that the efficiency of the health status monitoring function can be greatly improved using data reduction techniques on the telemetry data. It has been pointed out, however, that due to the complexity of current space power systems and the dynamics of the environments in which they operate, monitoring systems can no longer be static in nature. It appears that intelligent health status monitoring systems must go beyond complete rule-based systems to hierarchically structured model-based systems. Such an approach allows the inherent dynamics of the system itself, as well as the dynamics of the system in different contexts or modes, to be reflected in the monitoring system and the supporting data reduction subsystem or module.

It has also been shown that much of the reduction process should take the form of converting quantitative telemetry data to qualitative data. Knowledge-Based Systems gain their advantage because they can perform symbolic reasoning. Thus the best approach to data reduction for such applications is to process teh data using traditional computing environments with the goal of reducing the data to qualitative symbolic representations which can then be reasoned about in the knowledge base. Merging qualitative and quantitative data analysis in knowledge-based systems for EPS halth status monitoring is an area for further investigation.

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